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Does a Scopic Regime Erode the Disposition Effect? Evidence from a Social Trading Platform[☆]

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Abstract

A scopic regime constitutes a state of permanent reciprocal observation and scrutiny among participants. We investigate whether this environment reduces the disposition effect among retail traders as they are constantly scrutinized by others, thus driving them to realize and limit their losses. We use two anonymous data sets, the first from a popular social trading platform (STP) governed by a scopic regime, and the second from a traditional foreign exchange broker. STPs allow participants to interact and copy each other's trades using mirror trading, thus implicitly creating two groups; trade leaders who execute unique trades to build their performance record, and copiers who allocate funds to be managed by the former. We find ample evidence of a weaker disposition effect among trade leaders in the scopic environment compared to traders in a traditional setting. Our findings suggest that a state of constant observation and scrutiny erodes the disposition effect as individuals become more self-conscious of their actions and limit their losses to avoid tarnishing their public trading record.

Keywords: social trading, disposition effect, scopic regime, retail trading, foreign exchange, behavioral bias

JEL: C34, D53, F31, G20, G40, G41

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1. Introduction

"Cut your losses" is an expression said to encourage a person to stop wasting valuable resources on something that is deemed as failing. While this may seem evidently logical, some individuals do not quite abide by this prescription. Shefrin and Statman (1985) termed this phenomenon as the "disposition effect," which represents an investor's tendency to quickly realize gains and hold on to losses. This behavior, which has been extensively documented in the literature (Weber and Camerer, 1998; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Chen et al., 2007; Linnainmaa, 2010; Nolte, 2012), opposes rational economic models and has been shown to result in poor financial performance (Odean, 1998; Seru et al., 2010). Researchers have identified several cognitive illusions and emotional biases that contribute to the disposition effect, including mental accounting, loss-aversion, regret-aversion, self-control, and mean-reversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Odean, 1998). While these biases cannot be easily removed, individuals can still attempt to understand them and aim to prevent such predispositions by adopting a more systematic analysis of market conditions (Kahneman and Riepe, 1998). Consequently, correcting mechanisms may arise when one obtains a better understanding of circumstances (Wegener and Petty, 1995). Several studies have presented evidence showing that traders can learn from their past trading activities to reduce the disposition effect (Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Dhar and Zhu, 2006; Chen et al., 2007; Boolell-Gunesh et al., 2009; Seru et al., 2010). This argument is based on the idea that individuals would examine their ex-post performance and sensibly distinguish and attribute specific poor performing trades to their tendency to realize gains prematurely and hold on to losses, thus adjusting for the disposition effect. Nevertheless, what happens when individuals find themselves in an environment where their actions are constantly being scrutinized in real-time, and where poor performance may instantly tarnish their reputation? Under such conditions, traders may exhibit a heightened degree of self-consciousness such that they become more aware of the negative consequences associated with poor performance. Hence, traders would adapt their behavior as they tend to avoid displaying poor decisions by limiting losses instead of holding on to them — this can be achieved by realizing the loss on an open positions to avoid further loss — and seek to realize larger gains in order to showcase their superior trading skills. Consequently, an environment that promotes constant scrutiny is expected to erode the disposition effect.

In a traditional financial setting, institutional investors typically circumvent constant scrutiny by the use of formal structured contracts that outline how much and what type of information is disclosed on predetermined dates. For instance, mutual funds are generally required to disclose their holdings only on a quarterly basis (Haslem, 2007), while disclosure by hedge funds is voluntary (Anson, 2002). Moreover, individual traders in a traditional setting tend to keep their strategies and holdings private. In recent years, however, the rising popularity of social media has reshaped the way individuals access and participate in financial markets through new channels of communication, information sharing, and investing. One particular phenomenon that has attracted an increasing number of retail traders is social trading, which embeds the traditional online trading model into a social media network. This novel concept has been acclaimed for the high level of information transparency and disclosure that occurs in real-time, and the tools that are provided by these social trading platforms (STPs), which allow participants to interact with each other and even copy each other's trades using a mirror trading algorithm that is provided by the platform. We call this environment a "scopic regime," which designates a state of permanent reciprocal observation and scrutiny among participants (Knorr Cetina, 2003). We use this term in an interdisciplinary fashion to distinguish the trading environment on STPs from traditional trading settings. The notion of a scopic regime is meant to characterize the organization of an activity, such as trading, where participants reciprocally observe each other's actions and receive information in real time about the decisions of other participants. For instance, under the traditional organization of the trading floor, traders on the New York Stock Exchange could not directly observe the decisions of traders on the London Stock Exchange. Under a scopic regime, embodied by the integration of social media within the trading process, traders in London, New York, and elsewhere can reciprocally observe each other's actions in real time. Furthermore, there has been heightened interest in how participation in social media changes the attitudes, behavior, and the decisions of individuals. Experimental field studies conducted outside the sphere of finance show increased emotional contagion, as well as polarization of opinions among social media participants (Kramer et al., 2014; Coviello et al., 2014; Bail et al., 2018). Within the broader context of such findings, it is relevant to understand the impact of social media on decision making in financial markets.

Participants on STPs can be divided into two main groups, which we label as trade leaders and copiers. The former are typically aspiring money managers who invest the funds allocated to them by the latter in return for monetary compensation that may be directly or indirectly based on performance. Copiers can allocate their funds using the mirror trading algorithm by easily and explicitly copying the future trades of another participant with a click of a button, thus receiving a price identical to that received by the copied participant. Nevertheless, our study focuses on the behavior of trade leaders. We define a trade leader as an individual who only personally enters trades into the STP. In other words, a trade leader is someone who executes original trades and refrains from explicitly copying others.

Given this definition, we use a unique data set from a highly popular STP, which we call SocialTrade, with around 2.5 million trades executed by 77,476 trade leaders in 2013 to test whether exposure to a scopic environment decreases the disposition effect. We adopt two methods: 1) the disposition spread proposed by Odean (1998), which estimates a trader's propensity to realize gains relative to losses, and 2) the Cox proportional hazards model, which allows us to control for trade-specific characteristics. Furthermore, we compare the results obtained for trade leaders on SocialTrade to those of traders on an anonymous traditional online trading platform, which we call TradeStream, where trading activity is kept private. We use the full data sets as well as subsets with overlapping periods and common assets in order to examine whether the difference in disposition of traders between the two platforms is due to the characteristics of the trading environment. Data limitations do not allow us to identify and examine distinctly comparable subgroups of traders on the two trading platforms or control for demographic effects, such as age, gender and occupation among others. However, given the global popularity of SocialTrade, and the large number of traders in both data sets, we work on the assumption that traders on both platforms come from similar demographic distributions. In other words, traders on the two platforms are assumed to inherently have similar propensities to exhibit the disposition effect; thus any difference in disposition levels between the two platforms can be attributed to the effect of the trading environment. Supporting evidence for this assumption is provided by Heimer (2016) who finds no significant difference in the characteristics of traders between those who joined the STP and those who never joined.

In general, both methods show that trade leaders exhibit a weaker disposition effect compared to traders on the traditional trading platform. This evidence supports our argument that the scopic regime, through its state of constant reciprocal scrutiny, creates a correcting mechanism that erodes the disposition effect. As such, trade leaders under a scopic regime become self-conscious about their actions and more aware of the negative consequences associated with poor performance on their reputation, and thus choose to close losing positions in order to avoid holding unjustifiable paper losses.

On the one hand, our finding is in agreement with the popular argument in the literature that, while the disposition effect arises from cognitive illusions, individuals can learn and adjust their behavior in aim of preventing such predispositions (Kahneman and Riepe, 1998; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Dhar and Zhu, 2006; Chen et al., 2007; Boolell-Gunesh et al., 2009; Seru et al., 2010). Hence, correcting mechanisms develop as individuals become more conscious about their affinity towards holding on to a losing asset, prompting an alteration of their behavior from loss-averse to risk-averse (Wegener and Petty, 1995). In other words, the scopic regime results in an adjustment to the utility function of individuals, such that it is more symmetrical between losses and gains. Our paper shows that the scopic regime places individuals under a constant spotlight of scrutiny, and that this state gives rise to a heightened sense of self-consciousness, which makes individuals more aware of the financial as well as reputational risks associated with holding on to losing investments.

On the other hand, our results differ from those of Heimer (2016), who examines a sample of retail traders on an STP, and shows that social interaction contributes to the disposition effect. The author links this relationship to impression management, whereby a trader's self-image increases their tendency to exhibit the disposition effect since the appearance of success attracts attention to their profile and enables more persuasive interaction with others through peer-to-peer messaging. This argument suggests that the audience viewing the trader's profile primarily focuses on realized profits and disregards paper losses, even though the latter are displayed on the trader's profile. Contrastingly, the evidence in our paper shows that the scopic regime increases one's self-consciousness and awareness about exhibiting unjustifiable losses, such that they tend to realize and limit their losses. Nevertheless, there are several key differences between the datasets used by the author and the ones used in this study, which may explain the divergent conclusions.

First, Heimer (2016) uses data obtained from an STP, where retail foreign exchange traders can link their existing brokerage account to their social account on the STP. This process differs compared to that adopted by SocialTrade, which provides both the social as well as the brokerage services to traders, thus ensuring homogeneity with respect to the quality of services and price quotes. Nevertheless, Heimer (2016) finds that the effect of the STP environment on the disposition effect remains largely the same after controlling for brokerage fixed-effects.

A second key difference is that during the period of investigation in the author's study, the mirror trading feature was not yet available to traders on the STP.[1] This means that traders in the author's sample did not have a monetary incentive to build a performance reputation — as they do on SocialTrade — but instead only benefited from increased social interaction. While a growing social network and an increase in the number of peer-to-peer messages may add some positive utility with respect to an individual's reputation, we argue that a monetary incentive would have a more significant impact on one's reputation. In other words, traders are more likely to be self-conscious of and alter their behavior when there is a monetary reward (or penalty) compared to when the consequence is simply a change in the number of social interactions they encounter from anonymous individuals. In the sample used by Heimer (2016), traders did not have a monetary incentive to build a reputation, nor were they (directly or indirectly) penalized for poor performance. Since these traders did not have anything to lose in terms of financial remuneration related to reputation, they might not have deemed an outstanding unrealized losing position to have a significant detrimental impact on their reputation and compensation. In contrast, trade leaders on SocialTrade receive monetary compensation for superior performance, and are thus more likely to limit losses in order to avoid exhibiting any image of poor performance.

Third, the sample used by Heimer (2016) only includes participants who traded both before and after joining the STP, resulting in around one million transactions executed by 2,598 participants from early 2009 until December 2010. While such a sample setup controls for unobservable demographic characteristics between the control group (pre-joining the STP) and the test group (post-joining the STP), it results in selection bias since only traders who survived and opted to join the STP were considered in the analysis. As such, traders who survived are likely to have better performance through realized gains, which contributes to a higher disposition effect. Moreover, these individuals may have

[1] The author has confirmed that mirror trading was not available on the STP during the time of his study, but was introduced at a later stage.

altered their behavior over time by learning from their past experiences. On the contrary, our study employs two separate data sets of traders who trade in an overlapping period. Nevertheless, we make a key assumption that the two data sets have equivalent demographic distributions, and individuals on both platforms inherently exhibit similar psychosocial tendencies. This implies that any difference in behavior between the two platforms can be attributed to the effect of the trading environment.

Finally, with respect to the methodology, Heimer (2016) applies a discrete-time model, where the dependent variable is recorded at ten-minute intervals, and takes the value of one if the trader reduced his holdings in the asset and zero otherwise. We argue in section 3.2 that the time interval used is arbitrary and may lead to loss of information, especially when the transactions are time-stamped. Moreover, the author uses trader fixed-effects, which may lead to model overfitting. In this study, however, we use a continuous-time Cox model with trader random-effects.

The remainder of this paper is organized as follows. Section 2 gives a detailed description of social trading platforms. Section 3 presents the two empirical methods that are used. Section 4 presents the descriptive statistics for the two data sets. Section 5 is dedicated to the discussion of the results. Finally, section 6 concludes the study.

2. Mechanics of STPs

STPs are founded on the notions of complete disclosure and free flow of information regarding participants' profile details as well as their current and historical trading activities. This differentiates STPs from traditional financial environments and financial institutions, such as mutual funds and hedge funds, where performance is only disclosed quarterly by the former and voluntarily by the latter. The high level of mandatory disclosure on STPs facilitates the constant scrutiny of traders, which is an environment we call a scopic regime, and has attracted a growing crowd of retail traders towards a more transparent market. While the main goal of STPs is to promote transparency, there is surprisingly little information regarding the size of this market since this data is held by the STP firm, which typically does not want to disclose the size of its operations due to competitive reasons. In addition, the concept of an STP can take many shapes and forms, and is constantly changing[2], thus STPs can have different social trading features not only amongst each other, but also over time. Nevertheless, we provide some figures that are only a speculative estimate of the size of the STP market. The website Social Trading Guru lists 25 leading STPs that offered automated trade copying during 2017, with another nine platforms that focus on social networking and content aggregation only.[3] Some STPs publish the number users on their platforms, which can range from 100,000 to over seven million.[4] However, these figures often represent the number of registered accounts (i.e. opened accounts) and not the number of active traders, which can be significantly smaller and not as attractive to advertise.

STPs incentivize information sharing through compensation schemes where trade leaders can earn monetary benefits for managing their copiers' wealth. The compensation schemes offered by STPs can differ greatly, as they can depend on a range of key performance indicators (Doering et al., 2015). Some STPs adopt a performance-based compensation scheme where traders are rewarded depending on the return they generate for their copiers. Other platforms employ a *neo*-asset-based scheme that links the trader's remuneration to the number of copiers attracted, instead of the amount of assets under management. Doering et al. (2015) argue that the latter remuneration model decreases moral hazard as trade leaders have an incentive to build a good yet persistent track record in order to attract an increasing number of copiers. While STPs may change the models and metrics used for compensating traders, the scheme adopted by the STP in this study during the period of investigation is a function of the num-

[2]For example, the STP used by Heimer (2016) added the copy trading feature after the period investigated by the author.

[3]See `http://socialtradingguru.com/networks/social-trading-networks`.

[4]See `http://blog.thomasbrand.xyz/2017/10/19/what-does-social-trading-and-investing-mean-in-practice/`.

ber of copiers attracted, contingent on these copiers having a minimum balance and a certain number of trades executed per month.[5] This implies that the compensation offered by the STP in this study is not directly linked to performance, but rather to how skilled a trade leader is perceived by potential copiers. Hence, trade leaders are likely to become more aware of the financial as well as reputational risks associated with poor performance. The discussion about the compensation scheme serves to highlight the potential for increased sensitivity to reputational risk that individuals are subject to under a scopic regime — a risk factor associated with the potential loss of an entity's reputational capital, which has been found to significantly impact a fund manager's compensation in the hedge fund industry (Fung and Hsieh, 1999; Boyson, 2010).

In general, participants open an account on an STP that is directly linked to a brokerage account, or they can link their existing brokerage account to an STP, such as the platform used in the study by Heimer (2016). Next, they update their personal information on their profile page, which is publicly disclosed on the platform. Whenever participants execute a trade on an STP, they transmit a trade signal, which is defined as a set of rules to buy or sell a certain asset once the price reaches a predetermined level. The details of every trade are recorded on a participant's profile page in real time, such that all historical realized profits and losses as well as current unrealized profits and losses on open positions are publicly disclosed. This means that a trader's true performance is constantly on display, and cannot be gamed by simply deferring the realization of losses. We define a trade leader as an individual who only executes personal trades and refrains from explicitly copying the trades of others using the mirror trading algorithm provided by the platform. This group generally includes traders who aspire to become leaders by building their reputation and displaying their skills through the trades they execute. By doing so, they attract potential copiers in hopes of earning performance compensation depending on the remuneration

[5] We cannot provide specific details of these parameters without revealing the identity of the STP, which breaches our non-disclosure agreement.

scheme offered by the platform. Moreover, STPs usually use a proprietary ranking algorithm that enables them to feature the profiles of the top performing traders in real-time. This places these individuals in the spotlight and renders them highly susceptible to scrutiny.

Conversely, copiers are individuals who wish to have their capital managed by others. They evaluate the performance of trade leaders and identify those who adopt a trading strategy that best suits their own investment goals and risk appetite. Any additional information that copiers may wish to attain in order to reduce uncertainty concerning the identity and authenticity of the trade leaders can be collected via direct contact with the latter through instant messaging tools and discussion posts. This can result in a close, personal, and informal relationship between the parties involved. After copiers evaluate the profile and performance of the different trade leaders, they can then set up their accounts to automatically copy the trades of specific trade leaders in real-time using the mirror trading algorithm offered by the STP. In other words, trades executed by the trade leader are instantaneously executed in the copier's account at a price identical to that received by the trade leader, without the need for manual confirmation. Unless copiers choose to be involved in the daily investment process, it is unnecessary for them to interfere except for terminating the copying relationship. Conversely, if copiers choose to remain involved in the investment process but are unable to conduct a thorough investment analysis, they may decide to copy only certain trades after evaluating the rationale behind them by clicking on the copy button pertaining to each trade.

Trading on STPs requires opening a position via a standardized Contract for Difference (CFD) that is written on an asset, since traders on STPs do not trade the actual asset. A CFD is an electronic contract between a trader and a CFD provider (or broker), which entails that the trader relinquish physical possession of the underlying asset for a contract with the CFD provider who offers an identical economic exposure (Norman, 2009). CFDs are considered derivative instruments that enable traders to obtain exposure to, and speculate on the direction of the asset, without ownership requirements. The payoff from the CFD is equal to the difference between the price of the underlying asset at the time of opening the position and the price at which the contract is closed. Thus, a trader with a long (short) position in a CFD would profit if the price of the underlying asset rises (falls). Trading in CFDs implies that pocketing a gain or limiting a loss requires one to realize the open profit or loss, respectively, on a position. Moreover, CFDs are traded on margin, thus the trader may deposit an amount of capital that is significantly smaller than the asset's notional value, which may lead to exceedingly leveraged positions. Traders must constantly maintain a sufficient amount of capital in their accounts in order to satisfy the minimum required margin established by the broker, otherwise their positions may be liquidated.

3. Methodology

We employ two methods for estimating the disposition effect: the first was developed by Odean (1998) to calculate the disposition spread, and the second method is based on the Cox proportional hazards model.

3.1. Disposition Spread

To investigate whether the scopic regime decreases individuals' propensity to sell profitable trades and hold on to losing ones, we look at the frequency with which they realize gains and losses relative to their opportunities to close each of these positions. Following Odean (1998), we calculate for each trade leader i, during the trading period t the realized gains RG_t^i, paper gains PG_t^i, realized losses RL_t^i, and paper losses PL_t^i in terms of number of trades as well as net dollar values. It is important to note that most studies in the literature deal with institutional or individual investors who trade the actual asset, and who may hold the asset for a prolonged period. Moreover, the data employed by these studies show the quarterly holdings of these investors, thus the previously mentioned parameters are computed on a quarterly basis. In our study on the contrary, individuals on both platforms trade assets through CFDs, thus they do not hold ownership of the assets and they incur overnight fees for positions held until the next trading day.[6] Additionally, the high levels of leverage offered by the platforms allow traders to benefit from the slightest price swing, hence, trade durations tend to be short. Due to these reasons, calculating the above mentioned parameters based on a quarterly data frequency would result in inappropriate estimates of the disposition effect since traders in our data sets are highly likely to close their positions within a few days of opening them. To illustrate, consider a simple scenario with a single trader who buys two assets A and B on day one, and that both of these assets appreciate over the next few days. Assume that the trader closes his position in asset A on day one, and his position in asset B on day two. If we consider a trading period of one day, we would obtain count values for RG and PG equal to one and one, respectively on day one, and values of one and zero, respectively on day two. Averaging across these two trading periods would result in RG of one and PG of 0.5. Now, consider the scenario where the trading period is two days; thus, we would obtain count values for RG and PG of two and zero, respectively. As such, choosing a longer trading period in the context of short term trading would mean that most positions would have been closed, regardless of whether the trade was a win or a loss. This example clearly shows that the values computed for the realized and paper gains and losses are highly dependent on the trading period chosen. Due to this, we compute these parameters for different trading durations as a robustness check, where $t = [1 \rightarrow 7]$ days.

Next, we aggregate the abovementioned parameters across all trade leaders, and over all trading periods, in order to calculate the proportion of gains realized (PGR) and the proportion of losses realized (PLR). The two ratios can be

[6] While we do not have access to the overnight fees charged by the two platforms over the duration of the analysis, these fees tend to be highly similar across brokers especially in the foreign exchange market, since they are primarily derived from interbank interest rates. Given that the comparative analysis between the two trading environments focuses only on foreign exchange instruments, we work on the assumption that overnight fees on the two platforms are the same.

expressed as follows:

$$PGR = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(\frac{RG_t^i}{RG_t^i + PG_t^i}\right) \quad \text{and} \quad PLR = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(\frac{RL_t^i}{RL_t^i + PL_t^i}\right).$$

The overall disposition spread, $DISP$, is calculated as the difference between the two proportions such that $DISP = PGR - PLR$, where a large positive (negative) spread means that traders are more willing to realize gains (losses). The hypothesis to be tested is that traders tend to close winning positions and hold on to losing ones, provided that one uses a reasonable trading period. A one-tailed t-test can determine whether to reject the null hypothesis as follows:

$$t - statistic = \frac{(PLR - PGR) - 0}{\sqrt{\frac{PGR(1-PGR)}{RG+PG} + \frac{PLR(1-PLR)}{RL+PL}}}.$$

Note that the test for significance in this case counts each realized gain, paper gain, realized loss, and paper loss as a separate independent observation, which are then aggregated across all traders. This independence assumption may not hold perfectly in the context of social trading, where individuals may be tempted to imitate each other's trading activities (Gemayel and Preda, 2018). As such, the lack of independence will result in an inflated t-statistic; however, it does not bias the calculated proportions of realized gains and losses. Odean (1998) argues that when the test statistic is large enough, as presented in our results, some lack of independence is not problematic.

Odean (1998) proposes an alternative way of calculating the disposition spread by making different independence assumptions. Instead of assuming that independence exists at the trade level, we assume that it only exists at the trader level. This means that there may exist some form of relationship among the proportion of gains and losses realized within a trader's account but not across accounts. The PGR and PLR variables are calculated for each trader during every trading period, and are then differenced to obtain the $DISP$ spread. We then average this spread for each trader across all trading periods in order to obtain a disposition spread for each trader separately. PGR and PLR for each trader-period can be calculated as:

$$PGR_t^i = \frac{RG_t^i}{RG_t^i + PG_t^i} \qquad \text{and} \qquad PLR_t^i = \frac{RL_t^i}{RL_t^i + PL_t^i}.$$

While the first method of calculating the proportions of gains and losses realized weights each trader by the number of realized and paper gains and losses, this alternative method weights each trader account equally. As such, the latter method ignores the fact that traders who are more active and execute more transactions have more accurate estimates of their true PGR and PLR values. Going back to the subject of observation independence, choosing a short trading period may decrease the likelihood of having correlated trades within the same trading period; however, this manoeuvre in itself gives rise to another issue. To elaborate, we draw on our finding that trade leaders on SocialTrade and traders on TradeStream have weekly trading frequencies of 1 and 2.15, respectively. These figures amount to less than one trade a day. For simplicity, assume a trading period of one day, where a trader opens and closes one trade within a trading day. Hence, that trader would have either a PGR equal to one and PLR equal to zero if the trade was a win, or a PGR equal to zero and PLR equal to one if the trade was a loss. In these two scenarios, the $DISP$ spread will take on the value of either 100% or -100%. Odean (1998) notes that the proportions of realized gains and losses will be smaller for traders who trade frequently compared to those who trade less frequently. Hence, given that traders in our two data sets are not likely to have multiple trades opened at once within a very short trading period, this results in extreme values for the $DISP$ spread, which may not reflect the true disposition effect of the trader. Moreover, as the values of the parameters used in calculating the $DISP$ spread will be relatively low, this will result in a very low test statistic. While the test statistics may be somewhat biased and not very reliable when they are close to the traditional critical values of significance, the estimated disposition spreads are not, and provide a sensible starting point to investigate disposition differentials between the two data sets.

One drawback of the disposition spread is that it is not appropriate for cross-sectional comparisons due to the mechanical relationship between the disposition spread and the size of the portfolio (Odean, 1998; Cici, 2012). To illustrate, assume that trader A has a portfolio consisting of 12 winners and 12 losers, while trader B has a portfolio with three winners and three losers. Moreover, let both traders be equally influenced by the disposition effect, such that they are both twice as likely to realize a gain relative to a loss. Therefore, both traders would sell two winning assets and one losing asset, resulting in PGR and PLR values of $2/12$ and $1/12$, respectively for trader A, and PGR and PLR values of $2/3$ and $1/3$, respectively for trader B. Thus, the $DISP$ spread of trader B is four times that of trader A, despite both traders having the same propensity to realize winners relative to losers. The disposition ratio, denoted by $DISP\ RATIO$ and calculated as the ratio of PGR to PLR, overcomes this issue by correctly estimating the disposition to sell winners compared to losers.

Given the limitations of applying the disposition spread and ratio in the context of short term trading, we also adopt a survival analysis approach to estimate the disposition effect while controlling for trader characteristics and dependence among trades.

3.2. Cox Proportional Hazards Model

Survival analysis has been used by several studies to investigate the disposition effect, including Feng and Seasholes (2005) and Richards et al. (2017). We apply survival analysis techniques to measure the rate of event occurrence, which in our case is the closing of a trade, in relation to the "origin time" of the trade. Since our data includes trades that are executed at different points in time, survival analysis methods allow us to control for such left-truncated data, for which there is a systematic exclusion of survival times from the sample, and where the sample itself is dependent on the survival time (Allison, 2010).

Many of the techniques used in survival analysis assume that time is measured as a continuous variable; however, such an assumption may lead to computationally intensive processes. Some researchers have proposed using discrete-time models, where events are considered to occur at discrete time points. While this approach may be more computationally manageable, dichotomizing data over discrete time intervals may be highly arbitrary and wasteful of information (Allison, 1982). Heimer (2016) applies a discrete-time method by transforming timestamped transactions of traders into ten-minute intervals. This approach is arbitrary because the ten-minute interval does not hold any meaning, and it ignores the variation on either side of the interval cut-off point. For example, a trader who closes a position one minute after the trade exhibits a gain, and closes a losing position after nine minutes has a higher propensity towards realizing gains relative to losses. However, since both these trades are closed within the ten-minute interval in a discrete-time context, this does not allows us to differentiate between the disposition to close a position contingent on being a gain or a loss.

In order to avoid such subjectivity in selecting an appropriate discrete-time interval, we use a continuous-time model. Following the seminal work of Cox (1972), the general transaction-dependent Cox model used for modelling hazard rates is expressed as:

$$\begin{aligned} \lambda(t, X_i) &= \lambda_0(t) e^{\beta' X_i} \\ &= \lambda_0(t) \lambda_i \end{aligned}$$

where, $\lambda(t, X_i)$ is the hazard rate at time t conditional on a set of observed transaction-specific variables, X_i. The baseline hazard rate, $\lambda_0(t)$, is the hazard rate when all predictor variables are null. Since transactions executed by a trader may exhibit dependence, we incorporate into our framework unobserved individual heterogeneity. Given the set of i transactions that are executed by j independent individuals, we denote by b_j the random cluster effect that induces correlation among the transactions in the same cluster j, where we assume that the random effects $b_1, \ldots, b_j$ are i.i.d. random variables with $b_j \sim N(0, \sigma^2)$.

The mixed-effects Cox model is expressed as:

$$\lambda_{ij}(t, X_{ij}, Z_{ij}) = \lambda_0(t)e^{\beta' X_{ij} + b'_j Z_{ij}}$$

where λ_0 is an unspecified baseline hazard function, which is the hazard rate when all covariates take on the value of zero. X and Z are the design matrices for the fixed-effects and random-effects, respectively, and β and b are the fixed-effects and random-effects coefficients, respectively. The hazard rate, $\lambda_{ij}(t, X_{ij}, Z_{ij})$, is the probability density function of the event occurrence at time t conditional on the survival to that time.

The survival time in our study is computed in seconds as the difference between the closing and opening timestamps of each transaction. Moreover, all positions in both data sets have been closed, meaning that the hazard event has occurred for all observations. The predictor variables employed in the analysis include the following:

- *Gain*: a dichotomous variable to estimate the disposition effect, which takes the value of one if the transaction results in a gain and zero if it is a loss;
- *Long*: a dichotomous variable that takes the value of one for a long position and zero for a short position;
- T/P: a dichotomous variable that takes the value of one if the position is closed due to a take-profit order, and zero otherwise;
- S/L: a dichotomous variable that takes the value of one if the trade is closed due to a stop-loss order, and zero otherwise;
- *Leverage*: a categorical variable that captures the degree of leverage used based on the leverage levels offered by the trading platform[7]; and

[7] The TradeStream platform offers a fixed leverage ratio of 200 to one, hence we do not include this variable when fitting the models to this data set.

- $\log(Duration_{i-k})$: the log transformation of the duration of the previous k transactions.

We conduct a series of interrelated models on the two data sets. First, we fit Model (1), where we only use the $Gain$ variable in order to investigate whether there is a difference in the magnitude of the disposition effect between the two trading environments. Next, we run Model (2a) where we include $Long$, T/P, S/L, and asset fixed-effects as control variables and allow for interaction between the $Gain$ and the limit order variables. We run Model (2b) only on the SocialTrade data set, which further includes the $Leverage$ variable. Model (3) further includes monthly time fixed-effects. Model (4) further incorporates the $\log(Duration_{i-k})$ variable, where $k \in [1, 2]$.[8] Finally, Model (5) further includes trader random-effects. We conduct these analyses for each data set separately, and then repeat them for subsets that are selected by only considering the overlapping time frame and the common assets traded on the two platforms.

As a robustness check, we pool the data from the two platforms — we first do this for the full data sets and then for the common subsets — and create a dummy variable called STP that is equal to one if the trade was executed on SocialTrade and zero if it was executed on TradeStream. We then repeat the previously-mentioned models by including the STP parameter and its interactions with the other variables in order to explicitly estimate the effect of the trading environment on the hazard rate of the trade. All the results and conclusions obtained in the pooled analysis are similar to those reported for each data set separately. However, it is not feasible to estimate Model (5) using pooled data since there would be perfect correlation between the STP variable and the trader effects. In addition, our results show that after including trader effects, the $Gain$ coefficient changes significantly for all data sets considered, which highlights the importance of accounting for this effect. Thus, due to spatial limitations, the largely similar results and conclusions we obtain for the

[8]Adding higher order autoregressive terms of the $\log(Duration)$ variable does not impact the significance of the parameters, nor does it improve the explanatory power of the models.

separate and pooled analyses, and the infeasibility of including both platform and trader effects, we do not report the results of the pooled regressions and instead focus the discussion on each data set separately.

For all the estimated models, we report the concordance index or Harrell's C, which is one of the most widely used performance metrics for survival models (Harrell, 2013). This measure is interpreted as the probability of concordance between the predicted and the actual survival times (Harrell et al., 1982). We also report the Pseudo-R^2, which is calculated as $1 - exp((\chi^2_{LR})/n)$, where χ^2_{LR} is the chi-square statistic for the likelihood ratio test for the overall model, and n is the total number of observations.

A final note regarding the Cox model used in this study is that it ignores the price path of assets — which is also a drawback of the disposition spread. This means that we do not capture the behavior of the trader between the opening and closing times of a trade. For example, consider an open position where the profit alternates between a gain and a loss with an equal probability as the price of the asset fluctuates. One might claim that a trader exhibiting the disposition effect would realize the gain at the first occurrence. Nevertheless, we argue that the ultimate decision of the trader, manifested by the closing of the position, represents the true disposition of the trader. Hence, even if a trader had one position displaying a loss and another displaying a gain throughout their durations, with both positions being finally closed at a gain, this means that the trader has a tendency to realize gains more than losses regardless of the price path of the asset. Tracking the open profit of all trades for all traders in our data sets requires a great deal of computational power and access to market price data from the two platforms, which is not available to us. Using a third party price source may not be representative of what traders actually observed on the platforms due to different order books, spreads, and trading activity. As such, we end this discussion here and assert that the decision to close a position by the trader represents their true disposition.

4. Data

To compare the disposition effect of traders under a scopic and a traditional trading environment, we use two unique proprietary data sets where the first is obtained from a popular STP, which we call SocialTrade, and the second from a traditional online retail foreign exchange broker, which we call TradeStream.

Data limitations in this paper do not allow us to identify and examine distinctly comparable subgroups of traders on the two trading platforms or control for demographic effects. However, given the global popularity of SocialTrade, and the large size of both data sets, we work on the assumption that traders on both platforms come from similar demographic distributions. Consequently, traders on both platforms are assumed to inherently have similar propensities to exhibit the disposition effect. This means that any variation in disposition levels between the two platforms can be attributed to the effect of the trading environment. Supporting evidence for our argument is presented by Heimer (2016) who shows that traders who join the STP early on are not statistically different from those who join later with regards to characteristics such as age, experience, location, and trading style. A similar conclusion was also found when the author compared his sample of traders prior to joining the STP to another sample of traders who never joined the STP. Hence, we adopt this evidence in support of our assumption that the demographic characteristics of individuals and their inherent tendency to exhibit the disposition effect are the same for traders on both platforms, regardless of when they open their trading account.

4.1. Data from SocialTrade

The first data set is obtained from an anonymous yet highly popular STP, which we call SocialTrade, and contains over 63 million trades executed by all participants during 2013. Participants can trade in a wide range of assets including currencies, commodities, equities, and indices. The STP records the details of each transaction, including the opening and closing prices, amount traded, leverage used, direction, as well as the opening and closing timestamps.

Since we aim to study the disposition effect of traders who execute personal trades and refrain from explicitly copying others, we select trade leaders by applying a strict criterion where only participants whose trades were all entered personally into the platform during 2013 are included in our sample. Note that traders can execute a mix of personal and copied trades; however, we consider these individuals to be copiers who allocate part of their capital to be managed by trade leaders, yet reserve a portion for personal trading.

The final sample contains around 2.5 million trades executed by 77,476 trade leaders. We present some descriptive statistics in Table I. Trades can be categorized based on the asset traded as follows: currencies constitute 83.14% of trades, whereas commodities, equities, and indices make up 11.21%, 3.6% and 2.05%, respectively. Moreover, around 63% of these trades are personally closed by the traders, while 22% and 13% are triggered by stop-loss and take-profit orders, respectively. Next, we compute several trading characteristics, which are first averaged across trades of each trader and then across all trade leaders. On average, we find that trade leaders engage in both long (66.11%) and short positions, and employ a leverage ratio of 175 to one. With respect to the duration of trades, trade leaders keep positions open for an average of six days. The average frequency of annual trades across trade leaders is around 34, which is considerably low compared to that of the full population of participants (207). This suggests that trade leaders are more aware of the impact of transaction costs on profits. Finally, we find that trade leaders are more specialized since they trade in a fewer number of assets (3.6 on average) compared to the full population of participants (6.5).

4.2. Data from TradeStream

The second data set is obtained from an anonymous foreign exchange broker, which we call TradeStream, and contains around 6.9 million trades in 22 currency pairs, executed by 22,545 traders over the period January 2011 to September 2013. TradeStream does not offer participants any social trading features such as mirror trading, thus we consider all trades to be unique. Around 66.48%

of trades are personally closed by traders while 14.41% and 19.11% of trades are closed due to stop-loss and take-profit orders, respectively. Moreover, we calculate several trader characteristics, which are first averaged across trades of each trader, and then across all traders. We present these statistics in Table II. On average, we find that 47% of a trader's positions on the TradeStream platform are buys, which is around 20% less compared to trade leaders on SocialTrade. We find that the average trade duration on TradeStream is around 1.19 days, which is less than the duration of trades on SocialTrade. This means that most traders on TradeStream are day traders who close their positions at the end of the trading day. As such, they tend to minimize their exposure to overnight fluctuations in prices. With respect to the average number of annual trades, we report a figure of around 111 trades, which is almost three times the value reported for trade leaders on SocialTrade. Given that traders on TradeStream are day traders, the higher trade frequency indicates that these traders seek to exploit intraday price swings. Finally, we find that traders on TradeStream trade in an average of 5.7 different currency pairs. While this number is low, indicating that these traders specialize in a few currencies, this figure is higher than that of trade leaders, meaning that traders on TradeStream have a wider scope when searching for trading opportunities to exploit.

5. Results

In what follows, we present the results obtained from the two methods discussed previously for each of the data sets.

5.1. Disposition Spread Results

5.1.1. No Trader Clustering

We begin by calculating the disposition spread, $DISP$, by aggregating the realized gains, paper gains, realized losses, and paper losses on the basis of both trade counts and dollar values across all transactions and traders, before calculating the proportions of gains and losses realized. This analysis is repeated by varying the trading period, $t = [1 \rightarrow 7]$, and the results are presented in Table III. We first conduct the analysis using all the observations in both data sets. Panel A shows that trade leaders on SocialTrade exhibit a positive and significant disposition spread irrespective of the trading period or the basis used to calculate the parameters. For example, the $DISP$ spread, PGR, PLR, and $DISP\ RATIO$ for $t = 1$, are 15.59%, 41.85%, 26.26%, and 1.73, respectively, when parameters are calculated based on trade count, and 3.85%, 8.6%, 4.75%, and 2.09, respectively, when parameters are based on trade dollar values. The disposition ratios for $t = 1$ indicate that positions exhibiting gains are between 1.73 and 2.09 times more likely to be closed compared to positions that are losing. We also point out that as the trading period increases, both the PGR and PLR converge towards 100%, and the $DISP\ RATIO$ converges to one. This is expected in the context of short term trading since all positions, regardless of profitability, will be closed when considering a long trading period.

Regarding traders on TradeStream, the results presented in Panel B of Table III show that, over the period January 2011 to September 2013, traders exhibited positive and significant disposition spreads, which are considerably greater than those reported for trade leaders on SocialTrade across all trading periods considered. For $t = 1$ the $DISP$ spread, PGR, PLR, and $DISP\ RATIO$ are 25.06%, 53.77%, 28.71%, and 2.52, respectively, when using trade counts, and 24.21%, 35.08%, 10.86%, and 7.94, respectively, when using dollar values. These results indicate that traders on TradeStream are between 2.52 and 7.94 times more likely to close a winning position compared to a losing one. All figures in Table III clearly show that traders on TradeStream exhibit a greater disposition effect compared to trade leaders on SocialTrade.

In order to conduct a more comparable analysis, we recalculate the disposition spread parameters using an overlapping time frame between the two data sets, from January 2013 to September 2013. Additionally, we only consider the common subset of the assets traded on the two platforms, which includes 16 currency pairs. In general, we obtain results and conclusions that are highly similar to the analyses on the full data sets. Thus, due to spatial limitations and to avoid repetition, we do not present these results in the paper.

All our findings show that, while both trade leaders on SocialTrade and traders on TradeStream exhibit the disposition effect, this bias is much more pronounced among the latter.

5.1.2. With Trader Clustering

We calculate the disposition spread and disposition ratio for each trader and then average them to obtain overall mean measures for each trading period. This allows us to account for potential dependence between trades of each trader. The results are presented in Table IV. Panel A shows the results for trade leaders on SocialTrade throughout 2013 and including all assets offered by the platform. While the PGR and PLR ratios are still high, these figures are closer to each other resulting in narrow disposition spreads across all trading periods, and even in a small negative spread when $t = 7$ based on trade dollar value. Moreover, all estimates are statistically insignificant as indicated by the low t-statistics, which is due to the low parameter values. For instance, the top part of Panel A in Table IV shows that the trade count of realized gains, realized losses, paper gains, and paper losses for $t \leq 6$ days are very small, which would result in an insignificant t-statistic. This is due to the fact that trade leaders on average have around one position open in a given week (see Table I). As such, these results should be analyzed with caution.

Regarding traders on TradeStream (Panel B), we find that the disposition spread is statistically insignificant when using trade count as the basis for calculating the gains and losses, but it is significant across all trading periods when using trade dollar values. This inconsistency may be attributed to the issue mentioned earlier, where the trade count parameters are very small such that they result in insignificant test statistics. Nevertheless, the $DISP$ spread based on trade dollar values for $t = 1$ is 12.39%, which is almost half the value obtained in the initial analysis where dependency among trades was not taken into account. Our results indicate that the disposition effect is only present in the traditional trading environment and not under the scopic regime.

For a more comparable analysis, we re-estimate the disposition spreads and ratios using an overlapping time-frame, from January 2013 to September 2013, and we only consider the common subset of the assets traded, as we did earlier. In general, we obtain results that are very similar to those from the analyses based on the full data sets; hence, we avoid repetition.

To summarize, we find that when dependencies among trades executed by the same trader are not accounted for, traders in both scopic and traditional environments exhibit the disposition effect. However, the disposition effect under the former regime is considerably lower compared to the traditional environment. Moreover, when dependencies among transactions are taken into account, the disposition effect of trade leaders on the STP becomes statistically insignificant, while the disposition effect of traders on TradeStream is only significant when using the trade dollar value basis, and is around half the estimate obtained when we do not cluster trades. While we recommend caution when analyzing these results due to the low trading frequency in the short trading periods, the evidence supports our argument that the scopic regime erodes the disposition effect.

5.2. Cox Regression Results

The results for the entire SocialTrade data set are presented in Panel A in Table V. Model (1) shows a positive and significant *Gain* coefficient of 0.04 and an odds ratio (O.R.) of 1.04, indicating that a profitable position increases the hazard rate of the trade by 4%, which is evidence of a small disposition effect. Next, we fit Model (2a) and find that the *Gain* coefficient increases to 0.14. Moreover, long positions increase the hazard rate by 4%, as indicated by the O.R. of the *Long* variable. Regarding limit orders, we find a negative relation between the take-profit, T/P variable and the hazard rate with an O.R. of 0.27, meaning that a take-profit order reduces the hazard rate by 73%. The relation persists even after accounting for the interaction between the T/P and *Gain* variables. This result may seem counter-intuitive at first since one would expect take-profit orders to increase the hazard rate as profitable positions are realized once the market price reaches the take-profit limit. However, the T/P estimate is the effect of take-profit orders on the hazard rate relative to trades that are manually closed by the trade leader. One explanation for this result is that trade leaders place wide take-profit limits, which would require a longer trade duration for the market price to trigger the order. As for stop-loss orders, we find that the S/L variable also has a negative effect on the hazard rate with an O.R. of 0.74, indicating that stop-loss orders decrease the hazard rate by 26%. Again, this can be explained by the wide stop-loss limits used by trade leaders, which would require a longer duration for the price to reach the stop-loss level. We argue that the wide take-profit and stop-loss levels are a strategic signalling mechanism employed by trade leaders where they forgo realizing small profits in hopes of winning big, which would be perceived as superior trading skill by potential copiers, while allowing for some flexibility for adverse price swings by placing a wider stop-loss limit.[9] In Model (2b), all previously considered variables have a similar expected effect on the hazard rate. With respect to *Leverage*, we find that the low leverage ratio of 5 to 1 decreases the hazard rate while higher ratios have a positive effect that increases linearly. These results are as one would expect since high leverage ratios translate into large price swings, which would accelerate trading activity by allowing trade leaders to realize sizable gains (or losses) within a shorter period of time. Model (3) further includes monthly fixed-effects, and the previously considered variables maintain a similar effect on the hazard rate. The O.R. of the *Gain* variable drops to 1.08; however, still providing evidence of a disposition effect. In Model

[9]In support of our argument, we find that trade leaders on SocialTrade place take-profit and stop-loss limits 0.04% above and 0.09% below the opening price of a trade, respectively, while traders on TradeStream place limits 0.001% above and 0.01% below the opening price, respectively. In dollar terms, trade leaders who use take-profit and stop-loss orders on SocialTrade have average dollar gains and losses of 30.44 and -65.88 per trade, respectively, while those on TradeStream show average gains and losses of 24.56 and -56.1 per trade, respectively.

(4), the O.R. of the *Gain* variable increases to 1.16, which is around double the percentage change on the hazard rate compared to Model (3). In addition, we find that the one and two lagged-trade log(*Duration*) variables reduce the hazard rate by 15% and 12%, respectively. This suggests that trade leaders tend to stick with a rather consistent trade duration, such that the current trade duration is likely to be long if previous trade durations were also long; nevertheless, this effect decays the higher the duration lag order. Finally, Model (5) captures heterogeneity among trade leaders and shows an O.R. of 1.31 for the *Gain* variable, meaning that a winning position increases the hazard rate by 31%. This result is evidence of the disposition effect, and is opposite to the conclusion we obtained using the method of Odean (1998) with trader clustering, which showed statistically insignificant results. Given the drawbacks discussed earlier about calculating the disposition spread in the context of short term trading, we argue that the Cox model is the superior alternative since it does not depend on an arbitrary trading time frame. The expected effects of all control variables are similar to what was previously reported in Model (4). Moreover, we report a concordance index and Pseudo-R^2 of 85.7% and 86.2%, respectively, which suggest a good model fit.

The results for the full TradeStream data set are presented in Panel B in Table V. Model (1) shows an O.R. of 1.75 for the *Gain* variable, which is significantly greater than that reported for trade leaders on SocialTrade and suggests that a winning position increases the hazard rate by 75%. In Model (2a), the O.R. of the *Gain* variable rises to 2.29, and we find a negative but small effect for the *Long* variable on the hazard rate with an O.R. of -0.01. Regarding limit orders, we report an O.R. of 2.17 for the T/P variable indicating that take-profit orders increase the hazard rate by 117% relative to market orders, which is in line with our earlier finding that traders on TradeStream use tight take-profit limits. Similarly for stop-loss orders, we show that this order type increases the hazard rate by a factor of 3.72, which is in line with our finding that traders on TradeStream place tight stop-loss limits. Model (3) shows that the O.R. for the *Gain* variable drops to 1.88 after accounting for time fixed-effects;

however, it is still significantly greater than the estimate obtained for trade leaders on SocialTrade. The coefficient estimate for the *Long* variable, which was previously negative but close to zero, turns positive and is equal to 0.04. As for the limit-order variables, they maintain a similar effect on the hazard rate as found in Model (2a). In Model (4), the coefficients of all previously considered variables maintain their expected effect on the hazard rate. In addition, we find that the one and two lagged-trade log($Duration$) variables reduce the hazard rate by 17% and 13%, respectively. This indicates that the duration of a trade is likely to be long if prior trade durations are also long; however, this effect decays the higher the duration lag order. Finally, Model (5) shows that the *Gain* O.R. increases to 2.37, which is significantly higher than the figure obtained for trade leaders on SocialTrade. This evidence supports our argument that the scopic regime erodes the disposition effect. All control variables exhibit a similar effect on the hazard rate as in Model (4).

For a more comparable analysis, we fit the Cox models using the subsets of the two data sets with an overlapping time frame, from January 2013 to September 2013, and we only consider the common assets offered by the two platforms. We obtain results that are very similar to those of the full data set analyses, thus we do not report them due to spatial limitations.

6. Conclusion

In this paper, we investigate the disposition effect of trade leaders on an STP, which is governed by a scopic regime where individuals are under a state of constant reciprocal scrutiny and where poor financial performance may tarnish one's reputation and adversely impact future compensation. Specifically, we argue that the scopic environment induces a heightened sense of self-consciousness among traders, such that they become instinctively aware of the financial and reputational risks associated with displaying poor performance. As a result, traders would choose to close losing positions in order to avoid holding unjustifiable paper losses, while aiming to realize larger gains in order to publicize their superior ability. To test this, we use a data set from a popular STP, which we call SocialTrade, containing around 2.5 million transactions executed by 77,476 trade leaders, and another data set from a traditional trading platform called TradeStream, which contains around 6.9 million transactions executed by 22,545 traders.

We apply two empirical methods that are used in the literature. Using the measure proposed by Odean (1998), we first calculate the disposition spread without accounting for dependence among trades and find that, while traders on both platforms exhibit the disposition effect, traders in the scopic environment show a lower bias. When we cluster the trades per trader, we only find evidence of the disposition effect for traders on TradeStream. The second empirical method employs a series of Cox proportional hazards models, where we find evidence of the disposition effect for traders in both trading environments. Nevertheless, we find that the disposition effect of traders in the traditional financial environment is around two to four times larger compared to that of traders in the scopic environment.

While there are some differences in the results generated by the two methods, the overall comparative conclusion remains same. Specifically, we find ample evidence showing a weaker disposition effect for traders in a scopic environment compared to traders in a traditional trading setting. The results support our argument that the scopic regime, through its state of constant reciprocal scrutiny, erodes the disposition effect whereby individuals become more self-conscious about their actions and instinctively aware of the negative consequences associated with poor performance on their reputation. Consequently, they choose to close losing positions in order to avoid holding unjustifiable paper losses, while seeking to realize larger gains as a mechanism to signal their superior ability to potential copiers. Our results challenge those presented by Heimer (2016). However, there are several key differences in the empirical models used and in the features of the STP employed by the author compared to this paper, which may explain the divergent conclusions. In particular, we underscore the fact that during the period of investigation in the author's study, the STP did not offer traders the mirror trading feature which would allow them to manage the wealth of others. Hence, these traders did not have a monetary incentive to build a performance reputation and attract copiers — as is the case for trade leaders on SocialTrade — which is a factor that we argue is highly significant in shaping the behavior of traders. As a consequence, trade leaders on SocialTrade have a greater sense of awareness of the negative impact of displaying poor outstanding performance on reputation and compensation, due to the increased sensitivity to reputational risk that they are subject to under a scopic regime. Future research is encouraged to investigate how different social trading settings and tools affect trader behavior and performance.

Our finding contributes to the literature on prospect theory, which is based on the notion that gains and losses are valued differently; hence, individuals base their decisions on perceived gains rather than perceived losses (Kahneman and Tversky, 1979). This is due to the process by which individuals frame risky choices, thus leading to loss-aversion. While such a behavioral pattern is found among retail traders in general, we show that a scopic environment erodes the disposition effect, implying that when individuals are under constant observation, they alter their behavior from loss-averse to risk-averse. The result is an adjustment to the utility function such that it is more symmetrical between losses and gains. This occurs as traders choose to close losing positions, which reduces the risk associated with holding on to large unrealized losses. The rationale that the scopic regime induces risk-averse behavior among trade leaders as a mechanism to maintain status quo is also supported by evidence presented by Gemayel and Preda (2018). Specifically, the authors show that trade leaders under a scopic regime exhibit excess intentional herding as a risk-mitigation tool when 1) market information is scarce, 2) the risk (proxied by leverage) of a publicly-disclosed strategy is low, and 3) when they have more to lose by underperforming on large positions.

Data limitations in this paper related to social and demographic characteristics do not allow us to investigate comparable subgroups of traders in the two trading environments, or explicitly control for these characteristics. Moreover, we are not able to thoroughly investigate the relation between the disposition effect and performance measures, such as return on investment, due to lack of information on trader balances in both data sets. To illustrate this point, a gain of one unit for a trader with a balance of ten units represents an appealing 10% return on investment, while the same amount of absolute profit for a trader with a balance of 100 units translates into a return of 1%. Hence, the attractiveness of the same amount of absolute profit may be very different for two traders, and this factor may play a significant role in determining an individual's tendency to realize the gain (or loss). We highlight these data limitations as potential opportunities for future research.

This study sheds light on how the exogenous characteristics of a financial environment can alter the behavior or traders. We show that constant scrutiny can make individuals more risk-averse as they choose to limit their exposure to losing investments. Such an implication may be valuable to traditional retail brokers and regulators, whose aim is to help individuals adopt a more effective risk management approach. By incorporating some of the social trading characteristics into traditional online platforms, such as publishing all trading activities, brokers would be creating a scopic mechanism that is driven by the collective scrutiny of all participants and that produces a risk-adjustment benefit at the individual level. Similarly, mutual funds and hedge funds may benefit by being more transparent with their clients about the performance of their holdings. Investors in these funds may put pressure on the fund managers to limit losses and reduce the overall volatility of the portfolio.

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Table I: **Descriptive Statistics of Trades Executed by Trade Leaders on SocialTrade During 2013.** The following table shows descriptive statistics of all trades executed by trade leaders on SocialTrade during 2013. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	2,498,532				
Number of Users	=	77,476				
Financial Instruments				**Trade Close Type**		
Currencies	=	83.14%		*Market*	=	62.76%
Commodities	=	11.21%		*Stop Loss*	=	22.04%
Indicies	=	3.60%		*Take Profit*	=	13.14%
Stocks	=	2.05%		*Rollover*	=	2.06%
	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	66.11%	175	6.08	34.18	1	3.61
Min	0.0%	1.0	0	1	0.02	1
Max	100%	400.0	347	14,672	282	71
St.Dev.	0.355	156.51	17.24	166.32	3.20	4.36

Table II: **Descriptive Statistics of Trades Executed by Traders on TradeStream From January 2011 to September 2013.** The following table shows descriptive statistics of all trades executed by traders from January 2011 to September 2013. The table presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	6,851,845				
Number of Traders	=	22,545				
Trade Close Type						
Market	=	66.48%				
Stop Loss	=	14.41%				
Take Profit	=	19.11%				
	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	47.00%	200	1.19	111.75	2.15	5.72
Min	0.0%	200	0	1	0.02	1
Max	100%	200	229.1	31,765	610.87	22
St.Dev.	0.164	0	3.39	382.02	7.35	4.65

Table III: **Disposition Spread for Trade Leaders on SocialTrade and Traders on TradeStream - No Trader Clustering.** The parameters *RG*, realized gain, *RL*, realized loss, *PG*, paper gain, and *PL*, paper loss are aggregated across all trades and traders prior to calculating the proportions of gains and losses realized, given by *PGR* and *PLR*, respectively. *DISP* and *DISP RATIO* represent the disposition spread and disposition ratio, respectively. Finally, the t-statisitc is presented to test for the significance of the disposition spread.

Panel A: SocialTrade - All assets - From January 2013 to December 2013							
Parameters are calculated based on trade count.							
t	1	2	3	4	5	6	7
RG	3,128	7,433	11,733	16,054	20,293	24,670	28,909
RL	1,905	4,541	7,175	9,816	12,374	15,141	17,880
PG	3,115	3,120	3,102	3,122	3,191	3,064	2,916
PL	4,499	4,501	4,532	4,552	4,610	4,541	4,221
PGR	41.85%	62.38%	76.26%	82.06%	85.52%	88.76%	90.76%
PLR	26.26%	44.98%	58.33%	66.29%	71.74%	76.31%	80.59%
DISP	15.59%	17.40%	17.93%	15.76%	13.79%	12.45%	10.17%
DISP RATIO	1.73	1.52	1.35	1.26	1.20	1.17	1.13
t-statistic	-18.74	-24.70	-31.23	-32.71	-33.23	-34.83	-32.63
Parameters are calculated based on trade dollar value.							
t	1	2	3	4	5	6	7
RG	55,264	154,244	251,732	352,896	445,360	547,560	646,198
RL	67,772	198,042	320,078	452,027	571,799	713,897	844,938
PG	833,017	835,434	822,391	828,329	832,224	821,547	795,648
PL	1,673,960	1,681,006	1,671,392	1,697,021	1,715,562	1,663,776	1,633,218
PGR	8.60%	19.19%	27.99%	34.73%	39.39%	45.12%	49.12%
PLR	4.75%	11.63%	17.83%	22.91%	27.12%	31.86%	36.34%
DISP	3.85%	7.56%	10.17%	11.82%	12.27%	13.25%	12.77%
DISP RATIO	2.09	1.85	1.68	1.61	1.50	1.44	1.39
t-statistic	-113.81	-164.42	-198.90	-225.77	-234.78	-254.06	-247.30
Panel B: TradeStream - All assets - From January 2011 to September 2013							
Parameters are calculated based on trade count.							
t	1	2	3	4	5	6	7
RG	3,605	8,130	12,626	17,168	21,725	26,196	31,066
RL	1,721	4,011	6,309	8,573	10,919	13,179	15,667
PG	1,449	1,435	1,443	1,434	1,471	1,434	1,517
PL	4,496	4,507	4,519	4,509	4,493	4,539	4,383
PGR	53.77%	71.95%	84.59%	87.82%	89.46%	90.32%	91.23%
PLR	28.71%	45.45%	57.79%	65.19%	70.24%	73.55%	76.55%
DISP	25.06%	26.49%	26.80%	22.64%	19.22%	16.78%	14.69%
DISP RATIO	2.52	1.99	1.66	1.40	1.32	1.25	1.21
t-statistic	-27.66	-37.39	-47.54	-47.11	-45.77	-44.61	-43.48
Parameters are calculated based on trade dollar value.							
t	1	2	3	4	5	6	7
RG	86,684	217,640	348,199	478,432	610,563	740,746	881,173
RL	-79,971	-245,032	-413,465	-575,946	-748,657	-906,691	-1,091,677
PG	127,673	126,356	127,233	125,215	126,702	126,175	139,138
PL	-934,734	-935,774	-937,786	-932,627	-939,505	-931,639	-926,258
PGR	35.08%	55.88%	69.48%	76.19%	79.56%	82.74%	83.61%
PLR	10.86%	23.70%	33.28%	41.09%	47.22%	51.92%	55.33%
DISP	24.21%	32.18%	36.19%	35.10%	32.33%	30.82%	28.28%
DISP RATIO	7.94	8.65	8.36	11.39	1.98	1.94	1.86
t-statistic	-225.04	-345.04	-463.24	-517.00	-532.82	-562.22	-557.97

Table IV: **Disposition Spread for Trade Leaders on SocialTrade and Traders on TradeStream - With Trader Clustering.** The parameters *RG*, realized gain, *RL*, realized loss, *PG*, paper gain, and *PL*, paper loss are aggregated for each trader individually prior to calculating the proportions of gains and losses realized, given by *PGR* and *PLR*, respectively. *DISP* and *DISP RATIO* represent the disposition spread and disposition ratio, respectively. Finally, the t-statisitc is presented to test for the significance of the disposition spread.

Panel A: SocialTrade - All assets - From January 2013 to December 2013							
Parameters are calculated based on trade count.							
t	1	2	3	4	5	6	7
RG	0.92	1.87	2.64	3.30	3.90	4.51	5.07
RL	0.56	1.14	1.62	2.02	2.38	2.77	3.13
PG	0.92	0.79	0.70	0.64	0.61	0.56	0.51
PL	1.32	1.13	1.02	0.94	0.89	0.83	0.74
PGR	21.55%	35.12%	43.10%	47.92%	50.86%	54.25%	56.71%
PLR	16.65%	29.05%	37.26%	42.70%	46.62%	50.99%	55.16%
DISP	4.90%	6.06%	5.84%	5.22%	4.24%	3.26%	1.54%
DISP RATIO	0.79	0.82	0.84	0.85	0.86	0.86	0.85
t-statistic	-0.12	-0.14	-0.15	-0.14	-0.12	-0.09	-0.05
Parameters are calculated based on trade dollar value.							
t	1	2	3	4	5	6	7
RG	16.25	38.87	56.67	72.62	85.53	100.01	113.24
RL	-19.93	-49.91	-72.06	-93.02	-109.81	-130.39	-148.07
PG	244.94	210.54	185.15	170.45	159.82	150.05	139.44
PL	-492.22	-423.63	-376.29	-349.21	-329.46	-303.87	-286.22
PGR	17.98%	30.18%	37.69%	42.41%	45.26%	48.91%	51.97%
PLR	14.91%	26.63%	34.52%	39.81%	43.51%	47.97%	52.57%
DISP	3.07%	3.54%	3.17%	2.60%	1.75%	0.94%	-0.61%
DISP RATIO	14.07	12.92	11.08	11.84	9.64	10.24	9.73
t-statistic	-1.08	-1.00	-0.83	-0.66	-0.44	-0.24	0.15
Panel B: TradeStream - All assets - From January 2011 to September 2013							
Parameters are calculated based on trade count.							
t	1	2	3	4	5	6	7
RG	2.04	4.01	5.66	7.25	8.78	10.22	11.77
RL	0.97	1.98	2.83	3.62	4.41	5.14	5.94
PG	0.82	0.71	0.65	0.61	0.59	0.56	0.57
PL	2.54	2.22	2.03	1.90	1.82	1.77	1.66
PGR	36.30%	53.75%	63.73%	69.65%	73.27%	76.22%	78.35%
PLR	23.14%	36.90%	45.54%	51.57%	56.40%	59.81%	63.32%
DISP	13.16%	16.85%	18.18%	18.08%	16.87%	16.40%	15.03%
DISP RATIO	1.18	1.26	1.28	1.29	1.27	1.27	1.24
t-statistic	-0.36	-0.51	-0.61	-0.67	-0.69	-0.72	-0.71
Parameters are calculated based on trade dollar value.							
t	1	2	3	4	5	6	7
RG	49.02	107.40	156.20	202.11	246.76	289.05	333.83
RL	-45.22	-120.92	-185.48	-243.30	-302.57	-353.81	-413.58
PG	72.20	62.35	57.08	52.90	51.21	49.24	52.71
PL	-528.60	-461.77	-420.70	-393.98	-379.70	-363.54	-350.91
PGR	33.96%	51.59%	61.81%	67.93%	71.61%	74.77%	76.55%
PLR	21.57%	35.12%	43.68%	49.60%	54.35%	57.76%	61.14%
DISP	12.39%	16.47%	18.13%	18.33%	17.26%	17.01%	15.40%
DISP RATIO	44.39	40.96	37.47	35.76	32.71	30.51	27.59
t-statistic	-2.68	-3.82	-4.66	-5.19	-5.34	-5.68	-5.53

Table V: **Disposition Effect Estimated Using the Cox Proportional Hazards Model.** The four panels in the table show the results of the Cox models for the full SocialTrade and TradeStream data sets, as well as for the subsets selected based on an overlapping time frame and on the common assets traded on the two platforms. Model (1) uses only the *Gain* variable. Model (2a) also includes the control variables *Long*, T/P, S/L, and asset fixed-effects (Asset FE). Model (2b) further includes *Leverage*, and is only estimated for the SocialTrade samples. Model (3) further includes monthly fixed-effects. Model (4) also includes two lags of the log(*Duration*) variable. Finally, Model (5) incorporates trader random-effects (Trader RE). We report the coefficients (Coef.), odds ratios (O.R.), and standard errors (S.E.), as well as the concordance index and the Pseudo-R^2 for each model.

Panel A: SocialTrade - All assets - From January 2013 to December 2013

	Model (1)			Model (2a)			Model (2b)			Model (3)			Model (4)			Model (5)		
	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.
Gain	0.04	1.04	0.001 ***	0.14	1.15	0.002 ***	0.11	1.11	0.002 ***	0.07	1.08	0.002 ***	0.15	1.16	0.002 ***	0.27	1.31	0.001 ***
Long				0.04	1.04	0.001 ***	0.07	1.08	0.001 ***	0.08	1.08	0.001 ***	0.05	1.05	0.001 ***	0.04	1.04	0.002 ***
T/P				-1.31	0.27	0.016 ***	-1.50	0.22	0.016 ***	-1.86	0.16	0.016 ***	-2.69	0.07	0.017 ***	-1.99	0.14	0.021 ***
$T/P \times Gain$				0.88	2.40	0.016 ***	0.98	2.68	0.016 ***	1.33	3.79	0.016 ***	2.21	9.11	0.017 ***	1.48	4.37	0.02 ***
S/L				-0.30	0.74	0.002 ***	-0.56	0.57	0.002 ***	-0.64	0.53	0.002 ***	-0.64	0.53	0.002 ***	-0.66	0.52	0.002 ***
$S/L \times Gain$				0.01	1.01	0.004	0.06	1.06	0.004 ***	0.14	1.15	0.004 ***	0.20	1.22	0.004 ***	0.20	1.22	0.007 ***
$Leverage_5$							-0.43	0.65	0.047 ***	-0.29	0.75	0.047 ***	-0.39	0.68	0.05 ***	-0.42	0.66	0.101 ***
$Leverage_{10}$							0.32	1.38	0.043 ***	0.36	1.43	0.043 ***	0.29	1.33	0.046 ***	0.21	1.23	0.073 ***
$Leverage_{25}$							0.87	2.39	0.043 ***	0.86	2.37	0.043 ***	0.74	2.10	0.046 ***	0.63	1.89	0.085 ***
$Leverage_{50}$							1.55	4.69	0.043 ***	1.49	4.42	0.043 ***	1.25	3.49	0.046 ***	1.12	3.06	0.085 ***
$Leverage_{100}$							1.96	7.11	0.043 ***	1.90	6.71	0.043 ***	1.63	5.08	0.046 ***	1.49	4.44	0.088 ***
$Leverage_{200}$							2.82	16.8	0.043 ***	2.69	14.7	0.043 ***	2.28	9.75	0.046 ***	2.12	8.37	0.089 ***
$Leverage_{400}$							3.34	28.3	0.043 ***	3.19	24.3	0.043 ***	2.61	13.6	0.046 ***	2.42	11.2	0.09 ***
$\log(Duration_{i-1})$													-0.16	0.85	0.001 ***	-0.15	0.86	0.001 ***
$\log(Duration_{i-2})$													-0.12	0.88	0.001 ***	-0.08	0.92	0.001 ***
Asset FE					✓			✓			✓			✓			✓	
Time FE											✓			✓			✓	
Trader RE																	✓	
N		2,498,532			2,498,532			2,498,532			2,498,532			2,396,034			2,396,034	
Concordance		52.7%			60.5%			72.2%			74.2%			78.9%			85.7%	
Pseudo-R^2		1.1%			14.73%			57.9%			60.3%			73.5%			86.2%	

(continued)

Table V - Continued

Panel B: TradeStream - All assets - From January 2011 to September 2013

	Model (1)			Model (2a)			Model (2b)			Model (3)			Model (4)			Model (5)		
	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.	Coef.	O.R.	S.E.
Gain	0.56	1.75	0.001 ***	0.83	2.29	0.001 ***				0.63	1.88	0.001 ***	0.65	1.92	0.001 ***	0.86	2.37	0.001 ***
Long				-0.01	0.99	0.001 ***				0.04	1.04	0.001 ***	0.05	1.05	0.001 ***	0.03	1.03	0.001 ***
T/P				0.78	2.17	0.002 ***				0.50	1.64	0.001 ***	0.37	1.45	0.002 ***	0.31	1.37	0.002 ***
$T/P \times Gain$				-0.65	0.52	0.003 ***				-0.38	0.68	0.001 ***	-0.31	0.73	0.003 ***	-0.25	0.78	0.002 ***
S/L				1.31	3.72	0.002 ***				1.13	3.11	0.003 ***	1.02	2.78	0.002 ***	0.99	2.68	0.001 ***
$S/L \times Gain$				-1.42	0.24	0.002 ***				-1.30	0.27	0.001 ***	-1.19	0.30	0.002 ***	-1.13	0.32	0.001 ***
$\log(Duration_{i-1})$													-0.19	0.83	0.001 ***	-0.15	0.86	0.001 ***
$\log(Duration_{i-2})$													-0.14	0.87	0.001 ***	-0.10	0.91	0.001 ***
Asset FE					✓						✓			✓			✓	
Time FE											✓			✓			✓	
Trader RE																	✓	
N		6,851,845			6,851,845						6,851,845			6,807,054			6,807,054	
Concordance		56.4%			64.4%						72.8%			81.8%			86.1%	
Pseudo-R^2		6.86%			22.13%						33.93%			66.27%			86.5%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$